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Robust Receivers Final Report

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Summary

Our work addressed the design of wavelet based robust detectors and classifiers for SAR based applications. We considered two types of problems. The first is due to defocusing or blurring resulting from phase distortions in the SAR image formation process. The second arises when attempting to classify the type of clutter occurring in SAR. To address the first issue, we developed a geometric design for robust detection. To achieve robust classification of clutter, we developed a wavelet packet base matching to families of random processes.

Geometric approach to robust detection In synthetic aperture radar (SAR) and inverse SAR (ISAR), a scatterer is located by its range and range rate, [Curlander & Mcdonough, 1991]. Processing the SAR/ISAR data is a challenge largely because the differential range and the differential range rate to each scatterer vary over the coherent aperture time required for azimuth resolution. It is common to refer to these effects as motion through resolution cells (MTRC), [Carrara, Goodman, and Majewski 1995, Brown & Frederick, 1969]. As a result of the phase errors induced by MTRC the images of targets are smeared out, the range-Doppler image is blurred and loss of resolution in the SAR/ISAR system occurs. The problem is made worse in fine resolution SAR/ISAR systems where targets extend over several radar cells. In general, the blurring effect is space-variant. This means that the blurred target template is different for different target locations. This space-variant blurring effect is a major challenge to SAR target detection.

The performance of a detector optimally designed for one target template (target assumed at a given location) will deteriorate because the target may be a different location, consequently exhibiting a different template. It is important to develop detection algorithms that are robust to the smearing effects caused by MTRC.

Ways of handling the MTRC include accurate phase compensation during the image formation process. For example, see for example [Carrara, Goodman, and Majewski 1995], in spotlight SAR, the polar format algorithm (PFA) and the range migration algorithm (RMA), the extended coherent processing algorithm (ECP) or the enhanced image processing algorithm (EIP), [Ausher, Kozma, Walker, Jones, & Poggio, 1984], are designed to compensate for the MTRC. Other algorithms for SAR/ISAR MTRC compensation include [Wu & Vant, 1984], [Werness, Carrara, Joyce, & Franczak, 1990], [Jain & Patel, 1992], and [Berizzi & Corsini, 1996]. For a discussion on motion compensation algorithms for stripmap SAR see [Carrara, Tummala, & Goodman, 1995]. These algorithms are usually computationally complex because their implementation requires nonuniform interpolation in the Fourier transform domain. Implementing these algorithms in real time is out of reach for on-board processing of phase history data. It is desirable to avoid these costly interpolation techniques, see [Moore, 1996], [Beylkin, Gorman, Li, Fliss, &Ricoy95].

We focused our work on SAR systems. We considered a simple image formation algorithm like the rectangular format algorithm (RFA), which essentially involves inverse fast Fourier transforms and can be implemented in real-time, on-board the SAR platform. Of course such an algorithm leads to SAR images that are blurred and defocused. Our approach is to design detection algorithms that are robust to the type of blurring that arises under these circumstances. To succeed, we first modeled the blurring resulting

from the uncompensated phase due to MTRC. We demonstrated that the uncompensated image of a target could be described as a superposition of multiple space-shifted and scaled echoes of the fully compensated target image. This model provided us with a good characterization of the distortions. We finally used this model to design a detector that is robust to the spreading of the target over multiple echoes with arbitrary space shifts.

Our approach to designing the robust detector is geometrically based. We first define a signal set S that is the collection of the possible MTRC defocused target signatures. For important classes of SAR signatures, this set turns out to be a linear subspace. The optimal robust target detector is the generalized likelihood ratio test (GLRT) detector, [Scharf]. The GLRT detector determines the orthogonal projection of the observed SAR signature on this signal subspace. We say that the GLRT detector is matched to the signal set S. Finding this orthogonal projection involves the maximum likelihood (ML) estimation of the MTRC defocused image, which is a costly multidimensional nonlinear parameter optimization problem. Our strategy is to design a new subspace G that is close to the signal subspace S but such that the detector matched to G is simple to implement. We refer to G as the representation subspace. The closeness between S and G is measured by the gap metric, [Kato, 1976], [He & Moura, 1997], which is an appropriate measure for the similarity between two linear subspaces. We showed that the new robust detector is easy to implement and that it provides better performance than other alternative simple detectors commonly used in practice. We developed a wavelet-based subspace design algorithm to design the representation subspace G. Once we have the representation subspace G the new detector is easily implemented by taking inner products with integer shifts of a single function. Simulation results showed that the new focused detector provides significant gain over alternative detectors.

Matching wavelet packets approach to robust detection The second problem we considered in our research is the problem of robust terrain classification of land cover types in polarimetric SAR (POL-SAR). In these systems, the statistics describing the target terrains change. Variations in frequency, polarization, and observation angle induce changes in the radar-target phenomenology and yield multiple signatures for the backscatter from each terrain type, making the design of a single classifier that operates successfully on a wide spectrum of input data highly desirable. In our approach to robust classification, we developed a representative terrain model for each land cover type that serves as an aggregate description for the scattering behavior of a terrain under different circumstances. The robustness of the classifier to changes in terrain characteristics depends on both the tightness of the original cluster of signatures and the quality of the ensuing approximation. Since the former is dictated by empirically collected data, we addressed the latter constraint using wavelet-based representative processes. We developed an algorithm that designs the wavelet packet bases that best approximates a set (one or more) of random processes. Best is defined in the sense of minimizing the Bhattacharyya coefficient, which is a good metric to use in detection and classification problems.

Working with second order statistics, rewriting the Bhattacharyya distance in terms of the covariance, the problem of matching to a family of random process a wavelet packet base

is reduced to the design of wavelet packet based mean and covariance matrix. We developed two separate fixed-point algorithms that determine the set of eigenvalues for the wavelet-based covariance matrix and the accompanying mean vector. The unitary matrix of eigenvectors for the wavelet-based covariance matrix may be any of the admissible wavelet packet bases in the tree spawned by a wavelet/ scaling filter pair. The number of possible basis in a dyadic, orthonormal, wavelet packet tree is combinatorially large. We developed a best-basis search that optimizes the Bhattacharyya distance. We tested the algorithm with both synthetic data and POL-SAR data. The POL-SAR data is from the boreal ecosystem atmospheric study (BOREAS), and it is fully polarimetric (HH, VV, HV) at three frequencies (P-band, L-band, and C-band). This data was collected during the AIRSAR missions and have 1024 x 1279 pixels, each pixel corresponding to a resolution of 6 m x 12 m. We showed that the single Bhattacharyya distance based classifier operating on the basis of a process representative of the three polarizations data outperformed the Bayes classifier, i.e., the optimal classifier, operating on the basis of a single polarization (either HH or VV).

Transition During the course of this work we gave several talks at Northrop-Grumman ESSS Division in Baltimore-Washington. We worked with the Radar Systems Engineering Group. Two former students joined subsequently their group. Another student has joined Lincoln Laboratory.

Journal publications and Conference presentations We published five Journal papers and seven Conference papers detailing our results, see below.

Journal papers

- [1] Steve A. Benno and José M. F. Moura. "On Translation Invariant Subspaces and Critically Sampled Wavelet Transforms," Multidimensional Systems and Signal Processing, 8(1-2) pp. 89-110, January 1997. Special issue on wavelets and multiresolution analysis. Invited paper.
- [2] Chuang (Mike) He and José M. F. Moura, "Robust Detection With The Gap Metric," IEEE Transactions on Signal Processing," IEEE Transactions on Signal Processing, 45(6), pp. 1591-1604, June 1997.
- [3] Chuang He and José M. F. Moura. "Focused Detection Via Multiresolution Analysis," IEEE Transactions on Signal Processing, 46(4), pp. 1094-1104, April 1998. Special Issue on Theory and Applications of Filter Banks and Wavelet Transforms.
- [4] Steve A. Benno and José M. F. Moura. "Scaling Functions Robust to Translations," *IEEE Transactions on Signal Processing*, 46(12), pp. 3269-3281, December 1998.
- [5] Nirmal Keshava and José M. F. Moura. "Matching Wavelet Packets to Random Processes." IEEE Transactions on Signal Processing, 47(6), pp. 1604-1614, June 1999.

Conference papers

- [1] Nirmal Keshava and José M. F. Moura, "Wavelets and Random Processes: Optimal Matching in the Battacharyya Sense," 30th Asilomar Conference on Signals, Systems, and Communications, Monterey, CA, October 1996.
- [2] Chuang (Mike) He and José M. F. Moura, "Detection of Multipath Random Signals by Multiresolution Subspace Design," IEEE International Conference on Signal Processing, ICASSP '97, Volume V, pages 3701-3703, Munich, Germany, April 1997.
- [3] Nirmal Keshava and José M. F. Moura, "Terrain Classification Using Polarimetric SAR," IEEE International Conference on Signal Processing, ICASSP '97, Volume I, pages 555-557, Munich, Germany, April 1997.
- [4] Nirmal Keshava and José M. F. Moura, "Robust Classification of Targets in POL-SAR Using Wavelet Packets." IEEE National Radar Conference NATRAD '97, Syracuse, NY, May 1997.
- [5] José M. F. Moura and Chuang (Mike) He. "Target Detection in Unfocused SAR/ISAR Images, A Geometric Approach," IEEE National Radar Conference, NATRAD '97, Syracuse, NY, May 13-15, 1997.
- [6] José M. F. Moura and Chuang (Mike) He, "Focusing in Synthetic Aperture Radar by Multiresolution Methods," in invited session "Statistical Signal and Sensor Array Processing," IFAC Symposium on System Identification, IFAC-SYSID'97 SICE, volume 2, pp. 547-552, Kitakyushu, Fukuoka, Japan, 8-11 July 1997. Invited paper.
- [7] José M. F. Moura, "A Geometric and Multiresolution Analysis Approach to Robust Detection," IEEE 11th Workshop on Statistical Signal Processing, invited plenary talk, Orchid Country Club Singapore, August 6-8, 2001.

References

- [1] J. C. Curlander and R. N. McDonough, "Synthetic Aperture Radar," Wiley and Sons, New York, 1991.
- [2] W. G. Carrara, R. S. Goodman, and R. M. Majewski, "Spotlight Synthetic Aperture Radar," Artech House, 1995.
- [3] W. M. Brown and R. J. Fredirick, "Range-Doppler Imaging with Motion Through Resolution Cells," IEEE Transactions on Aerospace and Electronic Systems, 5(1): 98-102, January 1969.
- [4] D. A. Austerman, A Kozma, J. L. Walker, H. M. Jones, and E. C. Poggio, "Developments in Radar Imaging," IEEE Transactions on Aerospace and Electronic Systems, 20: 363-400, 1984.

[5] K. H. Wu and M. R. Vant, "A SAR focusing technique for imaging targets with random motion," in IEEE NAECON'84 Proceedings, 1984, pp. 289-295.

[6] S. Werness, W. Carrara, L. Joyce, and D. Franczak, "Moving Target Imaging for SAR Data," IEEE Transactions on Aerospace and Electronic Systems, 26(1):57-67, January 1990.

[7] A. Jain and I. Patel, "SAR/ISAR imaging of a uniformly rotating Target," IEEE Transactions on Aerospace and Electronic Systems, 28(1): 317-321, January 1992.

[8] F. Berizzi and G. Corsin, "Autofocusing of inverse synthetic aperture radar images Using Contrast Optimization," IEEE Transactions on Aerospace Electronic Systems, 22(3): 1185-1191, July 1996.

[9] C. Cafforio, C. Prati, and F. Rocca, "SAR Data Focusing Using Seismic Migration Techniques," IEEE Transactions on Aerospace Electronic Systems, 27:194-207, February 1991.

[10] W. G. Carrara, S. Tummala, and R. S. Goodman, "Motion Compensation Algorithm for Wideband Stripmap SAR," in *Algorithms for Synthetic Aperture Radar Imagery II*, D. Giglio, ed., Bellingham, WA, April 1995, SPIE, vol. 2487, pp. 13-23.

[11] T. G. Moore, "A New Algorithm for the Formation of ISAR Images," IEEE Transactions on Aerospace Electronic Systems, 32(2): 714-721, April 1996.

[12] G. Beylkin, J. D. Gorman, S. Li-Fliss, and M. A. Ricoy, "SAR Imaging and Multiresolution Analysis," in *Algorithms for Synthetic Aperture Radar Imagery II*, D. Giglio, ed., Bellingham, WA, April 1995, SPIE, vol. 2487, pp. 144-152.

[13] L. L. Scharf, "Statistical Signal Processing: Detection, Estimation, and Time Series Analysis." Addison-Wesley, Reading, MA, 1991.

[14] T. Kato, "Perturbation Theory for Linear Operators," Springer-Verlag, New York, 2nd Edition, 1976.